Simulator Ensembles for Trustworthy Autonomous Driving Testing

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Abstract Scenario-based testing with driving simulators is extensively used to identify failing conditions of automated driving assistance systems (ADAS) and reduce the amount of in-field road testing. However, existing studies have shown that repeated test execution in the same as well as in distinct simulators can yield different outcomes, which can be attributed to sources of flakiness or different implementations of the physics, among other factors.

In this paper, we present `MultiSim`, a novel approach to multi-simulation ADAS testing based on a search-based testing approach that leverages an ensemble of simulators to identify failure-inducing, simulator-agnostic test scenarios. During the search, each scenario is evaluated jointly on multiple simulators. Scenarios that produce consistent results across simulators are prioritized for further exploration, while those that fail on only a subset of simulators are given less priority, as they may reflect simulator-specific issues rather than generalizable failures.

Our case study, which involves testing a deep neural network-based ADAS on different pairs of three widely used simulators, demonstrates that `MultiSim` outperforms single-simulator testing by achieving on average a higher rate of simulator-agnostic failures by 51%. Compared to a state-of-the-art multi-simulator approach that combines the outcome of independent test generation campaigns obtained in different simulators, `MultiSim` identifies 54% more simulator-agnostic failing tests while showing a comparable validity rate.

To avoid the costly execution of test inputs on which simulators disagree, we propose in addition an enhancement of `MultiSim` that leverages surrogate models to predict simulator disagreements and bypass executions. Our results show that utilizing a surrogate model during the search does not only

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increase the average number of valid failures but also improves its efficiency in finding the first valid failure. These findings indicate that combining an ensemble of simulators during the search is a promising approach for the automated cross-replication in ADAS testing.

Keywords. Search-based software testing, scenario-based testing, autonomous driving, testing deep learning systems, simulator-agnostic

1 Introduction

Advanced Driver Assistance Systems (ADAS) rely on perception systems like cameras and LiDAR, powered by deep neural networks (DNNs), for real-time tasks such as lane-keeping, object detection and image segmentation. While effective, these systems must operate reliably across diverse environments, yet training data cannot cover all possible scenarios [81]. Consequently, ADAS may encounter unseen inputs post-deployment, making DNNs highly sensitive to variations in road shapes, lighting, noise, and perspective shifts. These discrepancies can lead to ADAS prediction errors, misclassifications, and inaccurate segmentations, which may impact vehicle decision-making and compromise safety [20].

Validating the safety of ADAS through virtual testing with scenario-based simulation is the default option for companies [20, 81]. Simulators enable developers to quickly prototype ADAS and evaluate them across a wide range of challenging scenarios. In the literature, researchers have proposed automated testing techniques to expose failing conditions and corner cases [1,29,43,57,58, 64,69,89], using various open-source ADAS simulators, such as CARLA [26], LGSVL [71], BeamNG [8], and Udacity [86], or commercial close-source solutions, such as Siemens PreScan [72], ESI Pro-SiVIC [32], and PTV VIS-SIM [87].

However, the result of a test execution through a simulation environment only approximates the actual test outcome in the real world. Indeed, multiple studies have shown that simulation-based testing might produce inconsistent results both within-simulator, i.e., when the same test scenario is executed multiple times on the same simulator [5, 14], and across simulators [12, 16]. This phenomenon is known as test flakiness, and it is characterized by multiple runs of the same test exhibiting non-deterministic behavior (i.e., tests pass or fail non-deterministically). Test flakiness has been studied extensively in the software testing literature [66]. A study by Amini et al. [5] shows that test flakiness is quite common also for simulation-based testing of ADAS, potentially leading to a distrust in virtual testing, as also reported in the field of robotic simulation [3]. Possible causes of flakiness stem from uncertainties in the simulation environment to timing and synchronization in the interaction between the ADAS and the simulator [5]. In general, such sources of non-determinism are unknown and difficult to control, making the results of automated testing techniques, i.e., the failure-inducing test cases, unreliable.

Despite the significance of the problem, very few solutions have been proposed to mitigate test flakiness in simulation-based testing (beyond discarding flaky tests [14]). Amini et al. [5] used machine-learning classifiers to predict the flakiness of an ADAS test using few test runs. Another way to mitigate test flakiness is by combining the outcome of multiple simulators when performing a testing campaign. In particular, Biagiola et al. [12], proposed a multi-simulator approach to approximate the outcome of a test case on a digital twin. Their framework named *digital siblings* (`DSS` henceforth) executes two independent test generation algorithms on two simulators, generating two feature maps that characterize test cases executed on such simulators. Through the operations of migration and merge, the framework outputs a combined feature map that prioritizes *agreements* across simulators, i.e., when the same test case has the same outcome on different simulators. The intuition is that we can expect test cases where the two simulators agree to be more reliable, and hence less flaky, than those where the two simulators disagree. Although their results show that the combination of the two simulators is able to predict the failures of the digital twin better than each individual one, the drawback of the digital siblings framework is that test case execution outcomes on the two simulators are merged as a post-processing step. This way, the test generation algorithm runs the risk of evolving flaky tests as each test is evaluated only on a single simulator during the search, making the whole process inefficient.

In this paper we present a novel approach named `MultiSim`, which incorporates multiple simulators as an ensemble directly as part of the test generation process. In particular, we cast the testing problem as a multi-objective optimization problem, where we define, for each simulator, a fitness function that evaluates the quality of the ADAS under test. By minimizing the fitness values obtained from executing each test case in multiple simulators and minimizing the distance between these values, we direct the search towards failure-inducing tests, while simultaneously generating *simulator-agnostic*, i.e, reliable, tests since the respective outcomes on the two simulators are close to each other.

In our evaluation of `MultiSim` we used the state-of-the-art DNN lane-keeping model Nvidia DAVE-2 [15] as system under test, and three different and widely used simulators, namely Udacity, Donkey and BeamNG [5, 29, 38, 69, 80, 93]. In particular, we compare `MultiSim` with a single simulator approach, as well as with the `DSS` framework in terms of effectiveness, i.e., the number of simulator-agnostic failures each approach triggers given a fixed search budget, and efficiency, i.e., how quickly each approach generates the first simulator-agnostic failure.

Our results show that `MultiSim` identifies on average 70% valid failures across all simulator configurations, outperforming `DSS` with 65% and single simulator-based testing with 47%. Regarding the rate of simulator-agnostic failures, BD (i.e., BeamNG combined with Donkey) outperforms both single-simulator testing and `DSS`-based testing, except for `DSS`-BD, where it has a similar validity rate but identifies a significantly higher number of failures. Using an ensemble of simulators during search-based testing demonstrates

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efficiency comparable to testing with only one simulator. Compared to DSS, in the BD configuration, it achieves significantly better results, while in another comparison, i.e., BU (BeamNG combined with Udacity) is outperformed by DSS-BU. Finally, integrating a Random Forest classifier to predict simulator-related disagreements into MultiSim improves the effectiveness, leading to a higher median of simulator-agnostic failures, as well as a lower standard deviation, compared to running the search without the classifier. Similarly, in terms of efficiency, we can identify a smaller median and variation in the search budget required for finding the first valid failure.

Our paper makes the following contributions:

- **Approach.** A novel search-based test generation approach called MultiSim that integrates multiple simulators to generate simulator-agnostic failures for ADAS.
- **Evaluation.** An extensive empirical study using three simulators and three different approaches showing that MultiSim is effective at generating simulator-agnostic failures for a state-of-the-art lane-keeping ADAS. To encourage open research, our test generation approach and experimental data are available [84].

The outline of the paper is as follows: In Section 2, we present the preliminaries. In Section 3, we introduce the problem statement and the notion of simulator-agnostic failures. In Section 4, we present our test generation approach, followed by our validation strategy. In Section 5, we evaluate our testing approach in comparison with single-simulator based testing and a default multi-simulator based testing approach. In Section 6, we discuss the insights and clarifications regarding our approach. In Section 7, we outline the most important threats regarding the validity of our results. In Section 8, we present related work. We finally conclude in Section 9, with a summary and insights into future work.

2 Background

2.1 Simulation-based ADAS Testing

We consider Level 2 ADAS, as classified by the National Highway Traffic Safety Administration (NHTSA) [85], which perform vision-based perception tasks using data gathered by camera sensors of a vehicle. Particularly, in this paper we focus on ADAS that learn the *lane-keeping* functionality, critical component for the safe operation of self-driving vehicles, from human-labeled driving data.

In the early stages of development, ADAS undergo model-level testing [68]. This involves evaluating performance metrics such as accuracy, mean squared error (MSE), and mean absolute error (MAE) on an unseen test set, i.e., a dataset not used during training. This form of testing is analogous to unit

testing in traditional software development, helping test engineers identify inadequately trained models [34].

Following model-level testing, ADAS are subjected to system-level testing [22, 33, 78]. This phase assesses the impact on the entire decision-making process of an ADAS, ensuring that its predictions align with expected vehicle behavior. A typical system-level test, i.e., test scenario, involves generating a one-lane or two-lane road, each defined by a starting and an endpoint, with varying length, curvature, and number of turns [4]. While driving, the ADAS processes input images and generates steering commands. System failures occur when the vehicle deviates from system requirements, such as violating safety constraints, e.g., driving off the road or causing harm to other vehicles, the environment, or pedestrians [80]. These failures often stem from errors in the perception component [45, 46]. The testing objective is therefore to identify road topologies where the ADAS fails to maintain the vehicle in lane, either by driving off-road (for one-lane scenarios) or crossing the opposite lane (for two-lane scenarios).

System-level ADAS testing is primarily conducted in simulation environments using software-in-the-loop testing to ensure safety and minimize costs. This approach enables safe measurement, analysis, characterization, and reproduction of driving failures. Well-established ADAS simulation platforms include industrial platforms such as Siemens PreScan [72] or ESI Pro-SiVIC [32], whereas open-source solutions widely adopted by researchers include Udacity [86], Donkey Car's sdsandbox [25] (hereafter referred to as Donkey, for simplicity), and BeamNG [8].

2.2 Search-based Software Testing

Our framework uses the concepts behind search-based testing (SBST), a testing technique where the testing problem is modeled as an optimization problem to be solved with metaheuristic optimization techniques [59]. SBST is defined as follows:

Definition 1 A search-based testing problem P is defined as a tuple $P = (T, D, F, O)$, where

- T is the system under test.
- $D \subseteq \mathbb{R}^n$ is the search domain, where n is the *dimension* of the search space. The vector $\mathbf{x} = (x_1, \ldots, x_n) \in D$ is called test input.
- F is the vector-valued fitness function defined as $F : D \mapsto \mathbb{R}^m, F(\mathbf{x}) = (f_1(\mathbf{x}), \ldots, f_m(\mathbf{x}))$, where f_i is a scalar fitness function (or fitness function, for short) that assigns a quantitative value to each test input and $\mathbb{R}^m$ is the *objective space*, and m corresponds to the number of fitness functions. A fitness function evaluates how *fit* a test input is, assigning a *fitness value* to it.
- O is the oracle function, $O : \mathbb{R}^m \mapsto \{0, 1\}$, which evaluates, given the objective space of the fitness functions, whether a test passes or fails. A test that fails is called *failure-inducing*.

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For instance, a search based testing problem for the ADAS system from Section 2.1 is defined as follows: roads represent test inputs passed to the ADAS and the execution of the ADAS on a road is performed in a simulator yielding location traces. Location traces are used by the fitness function to calculate to each executed test input the maximal distance of the vehicle to the center line. The oracle function specifies that an execution is failing when the vehicle drives off the lane when the fitness function value is above a predefined threshold.

In our approach, solving such a search-based testing problem requires the definition of multiple fitness functions. We use the concepts of multi-objective optimization to solve the problem.

Definition 2 In search-based testing, a multi-objective optimization (MOO) problem is defined as:

$$\min_{\mathbf{x} \in X} F(\mathbf{x}) = (f_1(\mathbf{x}), \ldots, f_m(\mathbf{x}))$$

where f_i is a scalar fitness function and $X \subseteq D$ is called the feasible solution set. In general, a set of equality and inequality constraints is defined, which have to be satisfied by solutions in X. A solution $\mathbf{x}$ with $F(\mathbf{x}) = (v_1, \ldots, v_m)$ is said to *dominate* another solution $\mathbf{x}'$ with $F(\mathbf{x}') = (v'_1, \ldots, v'_m) \iff \exists v_i.(v_i < v'_i) \wedge \forall v_j.(v_j \leq v'_j)$, i.e., $\mathbf{x}$ is superior to $\mathbf{x}'$ in at least one fitness value and at least as good in all other fitness values. Consequently, a solution $\mathbf{x}$ is called Pareto optimal if no solution exists that dominates it. The set of all Pareto optimal solutions is called Pareto set PS.

3 Problem Definition

3.1 Non-determinism in Virtual Testing

Recent studies have shown that there are several of simulation platforms available for system-level testing, both commercially and open-source [44,52], with no consolidated omni-comprehensive solution. As multiple simulation platforms exist, researchers have started performing cross-replication studies of ADAS in different simulation platforms [5,16], to confirm the testing results obtained on a driving simulator on another, possibly independent, simulator. Ideally, when we execute the test input on the same ADAS in the different simulators, the pass/fail verdict should not change, providing trustworthiness to simulation-based testing. However, the results of these studies highlight the negative aspects of simulation-based testing for ADAS. In most cases, the results obtained in one simulator (e.g., the failure conditions) cannot be reproduced by another simulator [5,12,16]. These discrepancies can lead to a distrust in simulation-based testing, as reported by recent surveys [3,30].

An example is shown in Figure 1, in which we replicated the execution of a logical test scenario for a lane-keeping ADAS model on three simulators, namely Udacity [86], Donkey [82] and BeamNG [8]. The logical test scenario

(a) Udacity.   (b) Donkey.   (c) BeamNG.

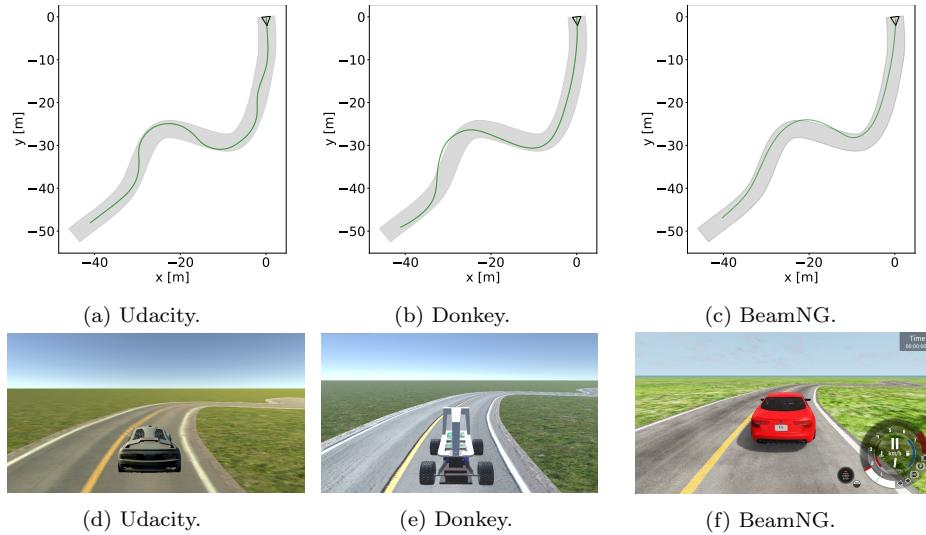(d) Udacity.   (e) Donkey.   (f) BeamNG.

Fig. 1: Difference in executing a lane-keeping ADAS on the same road in three different simulators, along with their rendering. In Udacity the trajectory of the vehicle (visualized in green, starting with a triangle) is within the lane's bounds while in Donkey and BeamNG the vehicle is departing off lane.

includes a two-lane 70 meters long road with three curves, one on the right with curvature 0.24, followed by one on the left with curvature 0.22, and one on the right with curvature 0.08. The objective for the ADAS model is to keep the car within the right lane from the start of the road until the end. The figure depicts only the right lane and shows that the driving behavior of the lane-keeping ADAS model (shown by the green line trajectory) is quite different across simulators. While the car reaches its destination in all three examples, it yields different simulation traces, specifically failing in the Donkey and BeamNG simulators but not in Udacity.

Potential root causes are related to flakiness in the simulation environments, bugs in the simulator, or synchronization issues in the communication between the simulator and the testing framework [5, 16, 44, 52]. As the simulation platform is used as-is, as a runtime testbed, it is usually not possible for developers to debug such issues, even less try to fix the simulator. This motivates the development of approaches to increase the reliability of simulation-based testing of ADAS, without requiring access to the simulation environments or its code, which is treated it as a black-box.

3.2 Simulator-agnostic Failures

In this paper, we focus on identifying test scenarios where failures are not caused by the limitations of the simulation environment but rather by defi-

ciencies in the system under test. To achieve this, we introduce the concept of *simulator-agnostic failures*.

Let us consider an ADAS $\mathcal{A}$ and a failing test input $\mathbf{x}$ that can be executed in a simulation environment $\mathcal{S}$. We define $\mathbf{x}$ as *simulator-agnostic* failure-inducing test input if $\mathcal{A}$ also fails on $\mathbf{x}$ when executed in a different simulator $\mathcal{S}'$ with equivalent capabilities. In other words, the execution outcome of $\mathbf{x}$ should not depend on compatibility issues between $\mathcal{A}$ and the simulators, i.e., $\mathcal{S}$ and $\mathcal{S}'$. This concept can naturally be extended to multiple simulators. In this study, we consider three simulation environments and assume that if a failure is consistently observed across all three, it indicates a true defect in the ADAS, as it is independent of any single simulator. Conversely, failures that occur only in specific simulators are regarded as *simulator-dependent*.

Following the established terminology from the deep learning testing domain [70], we refer to simulator-agnostic failures as *valid* failures, while we refer to simulator-dependent failures as *invalid* failures throughout this paper.

4 Approach

In the following, we describe our test case generation approach for ADAS using an ensemble of simulators. At the end of this section, we outline our validation approach to identify simulator-agnostic failures.

4.1 Ensemble-based Test Case Generation

Our proposed `MultiSim` approach incorporates the evaluation capabilities of multiple simulators to identify simulator-agnostic failures. The key idea is to apply ensemble learning within search-based ADAS testing, harnessing the strengths and compatibilities of individual simulators within a unified processing unit. In particular, to identify failure-inducing test inputs, `MultiSim` casts the testing problem as a multi-objective optimization problem, where evaluation results of multiple simulators represent objectives to be optimized. Instead of evaluating a test input in one simulator, `MultiSim` combines the test input evaluation results of multiple simulators in one evaluation vector. Our approach aims to obtain more reliable, and hence more valid, failure-inducing test inputs than a single-simulator approach that only evaluates a test input in a single simulator.

Our test case generation algorithm is inspired by the NSGA-II-D algorithm [75], which builds upon the well-established NSGA-II algorithm [24] while incorporating elements of novelty search [47]. To enhance diversity, the algorithm maintains an archive of previously discovered test cases, optimizing the distance between new and existing tests. Additionally, it leverages a re-population operator, originally introduced in `DeepJanus` [69], which replaces a subset of dominated test inputs in the population with newly generated ones, fostering continuous exploration of the input space.

Algorithm 1: Test case generation in `MultiSim`.

> **Input** : (T, D, F, O): An SBST Problem.
> $\quad\quad\quad S = \{S_1, \ldots, S_j\}$: A set of simulators, with $j > 1$.
> **Output:** C: Set of all failure-inducing test inputs.

1 INIT(T); $C \leftarrow \emptyset$; $A \leftarrow \emptyset$
2 $P_0 \leftarrow$ RANDOMSAMPLING(T, D)
3 $P_0 \leftarrow$ EVALUATEMSIM(P_0, S, F, T, A) /* Algorithm 2. */
4 **while** *budgetAvailable* **do**
5 $Par \leftarrow$ TOURNAMENTSELECTION(P_i)
6 $P_i \leftarrow$ CROSSOVERMUTATE(Par)
7 $P_i \leftarrow$ EVALUATEMSIM(P_i, S, F, T, A) /* Algorithm 2. */
8   **for** $\mathbf{x} \in P_i$ **do**
9 $T \leftarrow T \cup \{\mathbf{x}\}$ /* Store all evaluated tests. */
10 $P_i \leftarrow$ SURVIVAL(P_i, O)
11 $P_i \leftarrow$ REPOPULATE(P_i, D, T)
12 **for** $\mathbf{x} \in T$ **do**
13 $allFail \leftarrow \bigwedge_{k=1}^{j} O(f_k(\mathbf{x}))$
14   **if** *allFail* **then**
15 $C \leftarrow C \cup \{\mathbf{x}\}$
16 **return** C

Algorithm 1 details the steps of the `MultiSim` approach. The first step is to initialize the system under test T, the set of all failure-inducing test inputs C as well as the archive A (Line 1). Then, a random set of test inputs is sampled within the defined search domain (Line 2, P_0 being the initial population). In the next step, test inputs are evaluated based on the `MultiSim` specific evaluation function (see Algorithm 2). The main loop of the algorithm begins by applying default genetic operators such as selection, crossover and mutation (Lines 5–6). After the operators have been applied, a set of candidate test inputs to form the next population is defined. In particular, when all newly generated test inputs have been evaluated in the `MultiSim` specific evaluation function (Line 3), the survival operator is applied to rank the test inputs based on dominance (Line 10). Then, the re-population operator is used to replace a portion of dominated tests of each population by randomly generated ones to diversify the search (Line 11). When the search budget is exhausted, each test input is marked as failing, when all simulators agree on the failure of such test (Line 12–15). Practically, the oracle function O returns 1 for each simulator-specific fitness function $f_k(\mathbf{x})$, where $k : (i, \ldots, j) < m$ indicates the fitness function for each specific simulator (Line 13).

4.1.1 Multi-Simulator Evaluation

As detailed in Algorithm 2, in `MultiSim` the evaluation of a test input is defined as the fitness vector:

$$F(\mathbf{x}) = (f_1(\mathbf{x}), \ldots, f_j(\mathbf{x}), f_d(\mathbf{x}), f_a(\mathbf{x}, A)) \tag{1}$$

Algorithm 2: Test input evaluation in `MultiSim`.

Input : T : System under test.
$\quad\quad\quad$ $S = \{S_1, \dots, S_j\}$: A set of simulators, $j > 1$.
$\quad\quad\quad$ δ: distance threshold
$\quad\quad\quad$ P: Not evaluated test inputs.
$\quad\quad\quad$ A: Archive of test inputs.
Output: Q: Evaluated test inputs.

1   $Q \leftarrow \emptyset$

2   **for** $\mathbf{x} \in P_i$ **do**

3   **for** $S_k \in S$ **do**

4       $v_k \leftarrow$ SIMULATE$(\mathbf{x}, T, S_k)$ $\quad\quad$ /* Evaluate fitness for each simulator. */

5     $v_d \leftarrow \dfrac{\sum\limits_{k=1}^{j} \sum\limits_{l=k+1}^{j} |v_k - v_l|}{\binom{j}{2}}$ $\quad$ /* Compute average distance between fitness values. */

6     $v_a \leftarrow$ GETDISTANCETOARCHIVE$(\mathbf{x}, A)$ /* Compute distance w.r.t. archived test inputs. */

7     $\mathbf{x}.F \leftarrow (v_1, \dots, v_j, v_d, v_a)$ $\quad\quad$ /* Assign fitness values to test input. */

8   ADDTOARCHIVE$(\mathbf{x}, A, \delta)$

9     $Q \leftarrow Q \cup \{x\}$

10   **return** Q

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where (1) $f_1(\mathbf{x}) = v_1, \dots, f_j(\mathbf{x}) = v_j$ represent the fitness functions for the execution of $\mathbf{x}$ in simulator $S_1, \dots, S_j$ (Lines 3–4), (2) $f_d(\mathbf{x}) = v_d$ is defined as the average distance between the fitness values $f_1(\mathbf{x}), \dots, f_j(\mathbf{x})$ (Line 5), and (3) $f_a(\mathbf{x}, A) = v_a$ is the distance of the test input $\mathbf{x}$ to previously found test inputs in the archive A (Line 6).

While optimizing the functions $f_1(\mathbf{x}), \dots, f_j(\mathbf{x})$ prioritizes failure-revealing test inputs, minimizing $f_d(\mathbf{x})$ drives the search towards test inputs on which all simulators agree. The fitness function $f_a(\mathbf{x}, A)$ aims to diversify the search by calculating the distance of a test input to previously generated tests in the archive A [69]. As distance metric we the Euclidean distance between normalized test inputs. In particular, we apply Min-Max normalization, scaling values in the test input representation to a range from 0 to 1. By maximizing $f_a(\mathbf{x}, A)$ the goal is to identify more diverse test cases. After the evaluation of a test input is completed, it is added to the archive in case its distance to the closest test in the archive exceeds a predefined threshold δ (the function ADDTOARCHIVE in Line 8, takes care of comparing the current test input $\mathbf{x}$ with those in the archive A).

4.1.2 Test Representation

In the ADAS case study, a road is defined by so-called control points, which are used to perform Catmull Spline interpolation to obtain a smooth curve [4]. To be able to generate diverse and challenging roads we parameterize the road definition using the vector $\mathbf{x} = (\alpha_1, \dots, \alpha_n, l_1, \dots, l_n)$, where $a_i \in [-180; 180)$ denotes the clockwise angle between the i-th segment and the horizontal axis,
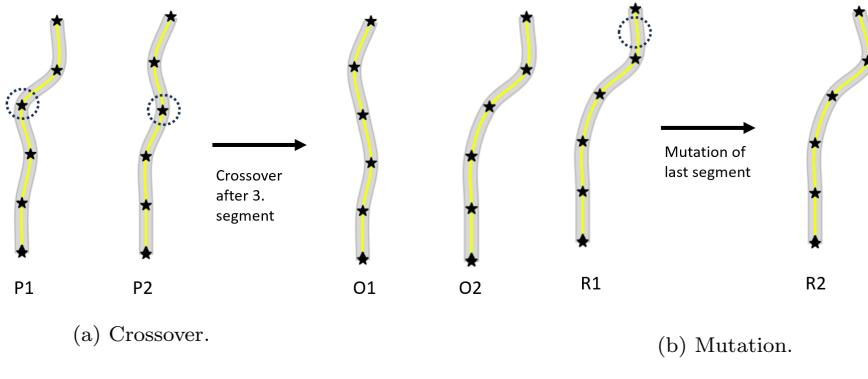
(a) Crossover.

(b) Mutation.

Fig. 2: Illustration of crossover (a) and mutation (b) of roads in `MultiSim` including control points which are placed within the road (visualized as stars). For sake of simplicity only angles are modified. In Figure a) tails of roads after the third segment are exchanged. In Figure b) the angle of the last segment is increased by 10 degrees.

while $l_i \in \mathbb{R}^+$ represents the length of the i-th segment between the control points c_{i+1} and c_{i+2}. For instance, the road in Figure 1a has 7 control points, 5 segments and is represented by the vector $(-90, -110, 173, -120, -140, 10, 20, 18, 17, 15)$.

4.1.3 Mutation/Crossover

Our implementation of the crossover operator on roads follows that of existing studies [36, 60]. Specifically, we use a one-point crossover operator, where for two given roads $\mathbf{p}_1$, $\mathbf{p}_2$ (i.e., the parents), we first randomly select an index, followed by exchanging the tail of the road $\mathbf{p}_2$, including segments with a lower index, with the tail of road $\mathbf{p}_1$, including segments with a higher index. Figure 2a illustrates the crossover of the road $\mathbf{p}_1$ with the road $\mathbf{p}_2$ resulting in the roads $\mathbf{o}_1$ and $\mathbf{o}_2$ (i.e., the offsprings), by exchanging the tails of the roads after the third segment.

The mutation of a road $\mathbf{x}$ is performed by randomly selecting a segment, followed by increasing or decreasing the angle, or the segment length, by a given amount. A mutated road can be invalid because of intersecting segments being placed out of the given map, or when violating a threshold which defines the maximum angle between segments. If a road is invalid, we randomly generate a new road by applying the same operator as used to generate the initial population for `MultiSim`. As an example, Figure 2b shows the mutation of a road $\mathbf{r}_1$ by increasing the angle of the last segment from $90°$ to $100°$.
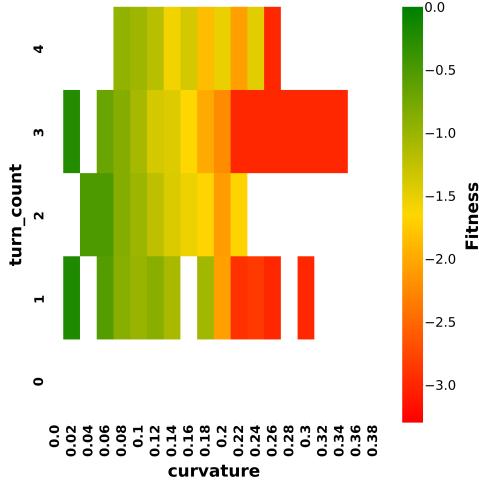
Fig. 3: Example of a feature map with two features, namely number of turns (i.e., `turn_count`) and curvature. The color of a cell is defined based on the worst *XTE* value of test inputs stored in a cell (colorbar on the right-hand side of the map). A cell is green when the *XTE* value is 0, red for the maximum, in absolute value, *XTE* value of -3. A cell is white if there is no test input that *covers* it. The fitness is negative, because the fitness function is to be minimized. In total 412 tests are stored in the feature map, which has 13 failing-cells and 35 non-failing cells.

4.1.4 Fitness Function

For the single evaluation of a test input in one simulator we use as fitness function the function f_{XTE}, which returns the maximal distance between the center of the car and the center of the lane (i.e., the cross-track error or *XTE* for short) over the whole execution time of the test input. We selected this function because it has been shown to be an effective fitness function for triggering failure-inducing test inputs [12, 36, 69]. As oracle function we use $O = f_{XTE} > d$ which evaluates a scenario execution as a failure when the maximal *XTE* value exceeds d.

4.2 Test Validation

This step aims to validate that the identified failing tests are not failing due to simulator-specific behaviors. To characterize the ADAS unique failures, we adopt the feature maps by Zohdinasab et al. [62, 93].

Feature Maps. In the first step of our validation approach, we map test inputs generated by `MultiSim` into a feature space [62,93], as it allows to repre-
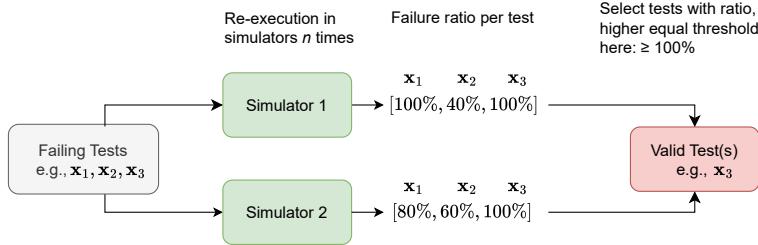
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Fig. 4: Validation of failure-inducing test inputs, i.e., $\mathbf{x}_1$, $\mathbf{x}_2$, $\mathbf{x}_3$. Each test is re-executed in multiple simulators, i.e., two in this case S_1 and S_2, and the failure rates for each test is computed. Then the failure rates on S_1 and S_2 are compared, and the test inputs are filtered according to a failure rate threshold. (in this case 100%). In this example, the only simulator-agnostic/valid failure-inducing test input is $\mathbf{x}_3$.

sent important characteristics of test inputs in a human-interpretable way. In particular, with a feature space we can discretize the multi-dimensional search space, which is the space of roads (see Section 4.1.2), for our lane-keeping ADAS, and consider diverse test cases for the evaluation of our approach. Our feature space is characterized by two static road attributes, i.e., *num of turns* and *curvature*, i.e., the reciprocal of the minimal value of the radius over all circles that can be placed through three consecutive control points of the road. Similarly to the fitness function, such choices of features were also found to be effective at characterizing the search space of road generators [93].

An example of a feature map is shown in Figure 3. A cell with the coordinates (x, y) contains test inputs whose curvature is in the range $[x - 0.02, \; x + 0.02]$, where 0.02 is the granularity of the map, and the number of turns is y. For instance, the road in Figure 1a is to be placed in the cell $(0.24, 3)$ as it has a maximum of curvature 0.23 and three turns. A cell of a feature map is colored based on the road with the best fitness placed in the cells, which is ranging from green (worst, $f_{XTE} = 0$) to red (best, $f_{XTE} = -3$) fitness value. We deem a cell as *failing* cell, when at least one test in the cell is failing w.r.t. the given oracle O. For instance, the cell $(0.32, 3)$ is a failing cell, while the cell at the position $(0.04, 2)$ is non-failing cell.

Re-execution. In the second step, we select failing cells from the feature map, extract a portion of failing and duplicate-free test inputs per cell, and re-execute each of these selected failure-inducing test inputs multiple times, to account for the flakiness of each specific simulation environment. Specifically, we execute such test inputs on simulators that have been not used by `MultiSim` during its search process, to confirm whether the failure-inducing test inputs generated by `MultiSim` are simulator-agnostic or not. For the validation we consider the notion of *hard* flakiness as defined by Amini et al. [5], where a test input is considered hard flaky when re-executing the test yields differ-

ent pass or fail verdicts. Figure 4 illustrates the validation approach, when employing two simulators for the validation. First, each failure-inducing test input is executed on each simulator for n times. For each execution the test input is evaluated based on the fitness and oracle functions (the same used during the test case generation process of `MultiSim`). Afterwards, a failure rate is computed. Finally, the failure rates are compared between the simulators for each test input to decide if the test is failing according to a user-defined threshold. For instance, in Figure 4 we have selected a 100% threshold, i.e., a failure-inducing test input is considered as simulator-agnostic if for every re-execution and for every simulator the test fails. In the example in Figure 4 only the test $\mathbf{x}_3$ is a simulator-agnostic/valid failure-inducing test input, as both simulators, i.e., simulator S_1 and S_2, report a 100% failure rate. For $\mathbf{x}_1$ a re-execution in S_1 yields a failure rate below 100%. Similarly, for $\mathbf{x}_2$ re-executions in both simulators S_1 and S_2, achieve failure rates below the threshold.

5 Empirical Study

In this section, we present the evaluation of our approach for identifying simulator-agnostic failures for a lane-keeping ADAS case study. We describe the research questions, our evaluation technique, evaluation experiments, implementation and results.

5.1 Research Questions

We consider the following research questions:

RQ$_1$ (effectiveness). *How effective is `MultiSim` in generating simulator-agnostic failure-inducing test inputs compared to single-simulator testing and a state-of-the-art approach?*

The first question evaluates the effectiveness of `MultiSim` in finding simulator-agnostic failures. After the test case generation phase, we validate a portion of failure-inducing test scenarios based on the approach described in Section 4.2.

RQ$_2$ (efficiency). *How efficient is `MultiSim` in generating simulator-agnostic failures compared to single-simulator testing and a state-of-the-art approach?*

The second research question allows us to evaluate whether `MultiSim` is efficient in identifying failures. Test efficiency is particularly relevant when the testing budget is limited [9].

RQ$_3$ (prediction). *To what extent can machine learning predictors increase the effectiveness and the efficiency of `MultiSim` in finding simulator-agnostic failures?*

Since simulator-specific failures, i.e., disagreements between simulators, might impact the identification of simulator-agnostic failures during the search, we use machine learning (ML) classifiers to predict whether a test input is leading to a disagreement between pass/fail verdicts on different simulators. We investigate whether this approach can be considered as a calibration technique

to fine-tune the original `MultiSim` approach to mitigate disagreements during the search caused by simulator-specific failures.

5.2 Baselines

We compare the performance of `MultiSim` to a search-based testing approach which only employs one simulator (`SingleSim`) during the search.

   We also compare with the recently proposed `DSS` approach [12], which employs multiple simulators by re-executing test inputs generated for one simulator in a different simulator and vice-versa. `DSS` is, to the best of our knowledge, the only existing approach in the literature that employs multiple simulators for automated test case generation.

5.3 Procedure and Metrics

To answer all three research questions for our case study, we first validate the failures as described in Section 4.2. Specifically, we assign all tests to cells of the feature map, by extracting curvature and number of turns of the corresponding roads, using a similar feature space granularity as proposed by Biagiola et al. [12]. We randomly select three failure-inducing test inputs from each failing cell. Preliminary experiments with a higher number of selected tests per failing cell, i.e., five, did not affect the results significantly.

   RQ$_1$. To answer RQ$_1$, to validate failures found by `MultiSim`, we use the third simulator that was not used during the search. We then re-execute each test five times to account for the flakiness of the simulation environment. As failure rate threshold we use 100%, i.e., a failure-inducing test input found by `MultiSim` is only valid if it always fails in a third simulator.

   To validate failures found by `SingleSim`, we use the same validation approach, but we use the two simulators that are not used during the search. For `DSS` we also use only one simulator for validation, as two of the three simulators available for our study are already used in the search. Based on the number of selected failures and the validation results, we assess the performance of `MultiSim`, `SingleSim` and `DSS` using two metrics: (1) n_valid, which is the number of valid failures, and (2) $valid\_rate$, which is defined as:

$$\text{valid\_rate} = \frac{\#\text{ valid failures}}{\#\text{ failures selected for validation}}$$

   RQ$_2$. To answer RQ$_2$, after validating all the selected failures, we identify at which time during the search each valid failure is encountered. We then select the first valid and failure-inducing test found, and compute the corresponding percentage of the search budget to find such failure.

   Specifically for `DSS`, as it consists of two independent search executions and two migration steps, we first identify in which simulation run the failure is

detected. Based on the order of the run executions and the evaluation number we compute the total run time to find the failure. That is, when a failure is detected in simulator DS1 with in total A test evaluations at the evaluation number a, while simulator DS2 performed in total B test evaluations, we assign to the test the final evaluation count as $A + B + a$. In case the valid failure is detected during the execution of B at evaluation number b, we assign to the test the evaluation count $A + B + A + b$, respectively.

RQ₃. To answer RQ₃, we select the configuration of `MultiSim` with the *best* results in terms of validity rate and number of failures, and collect test cases from past executions where the simulators both agree or disagree. In addition, we execute a modified version of `MultiSim` with five different seeds where the fitness function prioritizes disagreements. Specifically, we reuse Algorithm 2, but maximize $f_d(\mathbf{x})$, i.e., the distance between maximum XTE evaluations. We pass the roads as inputs and the labels representing an agreement or disagreement to five different and widely used ML classification models for training. Specifically, we use Decision Trees [18], Random Forests [17], Support Vector Machines [23], Logistic Regression [19] and Stochastic Gradient Boosting [27]. For the training of the classification models we use default hyperparameter configurations available in the Sklearn library.

We then evaluate the ML models based on F1-score, Precision, AUC-score, Accuracy. The best performing ML model on all metrics is then integrated into `MultiSim` and executed with the same search configuration as `MultiSim`.

In terms of metrics, we measure the number of valid failures (*n_valid*) and validity rate (*valid_rate*) as in RQ₁, and compare `MultiSim` with and without the integration of a disagreement predictor. We also measure the first valid failure as the efficiency metric for both approaches.

5.4 Experimental Setup

5.4.1 Simulation Enviroments

We have selected the following simulators for our study: BeamNG, Udacity and Donkey. We have chosen such simulators for the following reasons: 1) they seamlessly integrate with our lane-keeping ADAS case study, as the simulation environment, i.e., asphalt road on green grass and sunny weather, has been aligned [12] to be able to replicate the same simulation conditions across different simulators; 2) they are complementary as they differ in terms of the physics implementation or the rendering engine; 3) they are open-source or available under permissive academic-licenses (BeamNG). A brief description of the simulators provided is as follows:

– BeamNG is based on Unreal engine, implements soft-body physics, serves as the simulator in the SBFT competition [11, 28, 53], and it has been used extensively in the literature to benchmark testing approaches [8, 36, 69, 93].

– The Udacity simulator is a cross-platform and rigid-body physics developed with Unity3D [86]. While originally developed for educational purposes, it has been widely applied for ADAS testing [7, 12, 31, 37, 38, 76, 79].
– The Donkey Car Simulator is part of the Donkey Car framework that is used to build and test small-scale self-driving physical vehicles [25]. Similarly to Udacity, it implements rigid-body physics, and is developed with Unity 3D. The simulator is actively used in the literature for the validation of testing approaches [12, 48, 61, 77, 78].

In our experiments, we execute `MultiSim` in three different configurations: in the configuration BD we use BeamNG and Donkey as simulator ensemble, in the configuration BU we use BeamNG and Udacity, and lastly in the configuration UD we use Udacity and Donkey. We also evaluate `DSS` in such configurations; in the tables and figures below, we prefix such configurations with `DSS`- (e.g., `DSS`-BU indicates the configuration BU with the `DSS` approach, while BU indicates the same configuration with the `MultiSim` approach). It is noteworthy that in the original DSS paper [12] only the configuration `DSS`-BU was proposed and evaluated. The extension of the approach to other simulators constitutes a novel experimental contribution of our work.

5.4.2 Study Subject

We evaluate our approach on the DAVE-2 lane-keeping ADAS. DAVE-2 is a convolutional neural network developed for multi-output regression tasks based on imitation learning [15]. The model architecture includes three convolutional layers for feature extraction, followed by five fully connected layers. DAVE-2 has been extensively used in a variety of ADAS testing studies [12, 13, 38, 77, 83, 90]. The model takes as input an image representing a road scene, and it is trained to predict vehicle's actuators commands. Our implementation includes a DNN with learned lane-keeping capabilities, whereas the throttle of the vehicle is determined via a linear interpolation between the minimum and maximum speeds [12].

We use a pre-trained DAVE-2 model from previous work [12] that has been trained on more than 60,000 images and steering commands automatically by a PID-controlled autopilot driving the car on roads with different road complexity in the three simulators used in this work.

5.4.3 Search Setup

Search Algorithm. For the test case generation with `MultiSim` we use NSGA-II-D, integrated in Algorithm 1. For `SingleSim` we also use NSGA-II-D but employ only one simulator for the evaluation of the fitness value of a test case. We use the same hyper-parameter configuration for all algorithms, such as mutation, crossover rate and population size. To select the archive threshold δ that controls which test inputs shall be included in the

Table 1: Algorithm configuration for the approaches under test `MultiSim`, `SingleSim` and `DSS`. All configurations are equal across methods, beside the number of fitness functions used for `MultiSim`.

Parameter	SingleSim	MultiSim	DSS
Test Generator	NSGA-II-D	NSGA-II-D	NSGA-II-D
Population size	20	20	20
Time budget	6 hours	6 hours	6 hours
Mutation rate	1/10	1/10	1/10
Crossover rate	0.6	0.6	0.6
Archive distance	4.5	4.5	4.5
# Fitness functions	2	4	2
# Search variables	10	10	10

archive during search, we follow the guidelines of Riccio et al. [69] and perform preliminary experiments with different thresholds, ranging from 4 to 6. We assess the diversity of the corresponding feature map after the search, by identifying how many cells of the map are covered. As the archive threshold affects the diversity of the search, we use the coverage of the feature map to identify an appropriate threshold, which is 4.5 in our case. Further, we configure a maximum search budget of six hours for all testing approaches, which proved sufficient to explore the search space and obtain an adequate number of failures.

In the `DSS` approach, we also use NSGA-II-D for test generation. Test cases are produced through two independent search executions, each employing a different simulator, i.e., S_1 and S_2. The test cases generated by S_1 are subsequently re-executed in S_2, and vice-versa. A test case is classified as critical only if it has been evaluated as critical by both simulators. The results from both simulators, including all generated and migrated test cases, are then aggregated to represent the final output.

For `DSS`, we adapted the search budget for the search in two selected simulators before the test migration: we set it to a quarter of the total search budget, because first, two independent search runs are executed, and in the second step results have to be migrated in the respective simulator. The remaining parameters are set as for `SingleSim` and `MultiSim`. An overview of the complete configuration for all search methods can be found in Table 1.

Initial Population. To generate the initial population of roads, we use the test generator implemented in the study from Riccio et al. [69], where a road is iteratively generated while persevering the user-defined constraints such as segment length and maximum angle between consecutive segments. In particular the algorithm samples segments randomly based on the given maximum angle and segment length.

Mutation/Crossover. The mutation extent is randomly selected in the range of $[-8, 8]$, while the segment length is randomly set in the range $[10, 20]$.

Fitness/Oracle Function. As fitness and oracle functions we use the function f_{XTE} as defined in the motivation example. As oracle function we

use $O = f_{XTE} > 2.2$ that evaluates a scenario execution as a failure when the vehicle leaves the driving lane (similar to existing case studies [12, 35]). We stop the simulation on a given road when the current XTE value exceed a threshold of 3 mt, or the car reaches the end of the last segment.

5.5 ADAS Preliminary Evaluation

On the one hand, considering an ADAS model from previous work [12] mitigates the threats to validity of training our own model for testing. On the other hand, vision perception models like DAVE-2 are negatively affected by changes of image distributions [45, 46]. Thus, we assess the driving performance of the ADAS from previous work in our environment prior to the empirical evaluation. Specifically, we have defined 16 different types of roads with a road-wise maximum curvature ranging from 0 to 0.19, while the number of turns was in the range 1 to 4, and the road length was 100 mt. The evaluation allows us, on the one hand to investigate the flakiness of the simulation environments, and on the other hand to verify whether the testing setup including the hardware and software configurations is suitable for our study.

We executed the ADAS in every simulator on each of the roads for 10 times to account for the flakiness, and assessed the quality of the driving using the XTE fitness function. The results of this experiment with a detailed description of the roads used can be found in our replication package [84]. The results show that the ADAS exhibits low XTE variation (below 0.7m) across all roads without failing, even on roads with a high number of turns and high curvature. These observations suggest that while the vehicle's trajectories and driving styles are not harmonized across simulators, the ADAS's driving performance is not impacted by hardware limitations or latencies, as the variation is minimal and the ADAS does not fail. Thus, we conclude that the ADAS under test is sufficiently robust for exhaustive testing.

5.6 Implementation

We have implemented `MultiSim` using the testing framework OpenSBT [74]. OpenSBT is a modular framework that eases the execution, as well as the extension of SBT components for conducting testing experiments. OpenSBT has been recently applied for evaluating testing techniques and replication studies [64,73,75]. To implement our test generator in OpenSBT, we have extended the problem definition and test execution interfaces by evaluating a test input in multiple simulators and merging the result using a migration function. Our implementation allows to use any simulator and evaluation migration strategy, which is integrated into the framework. The code of `MultiSim` is available in our replication package [84].

All experiments have been executed on two computing devices, one PC with a Ryzen 5 5600X CPU, 32 GB RAM, and a 4090 Ti GPU, and on a Linux
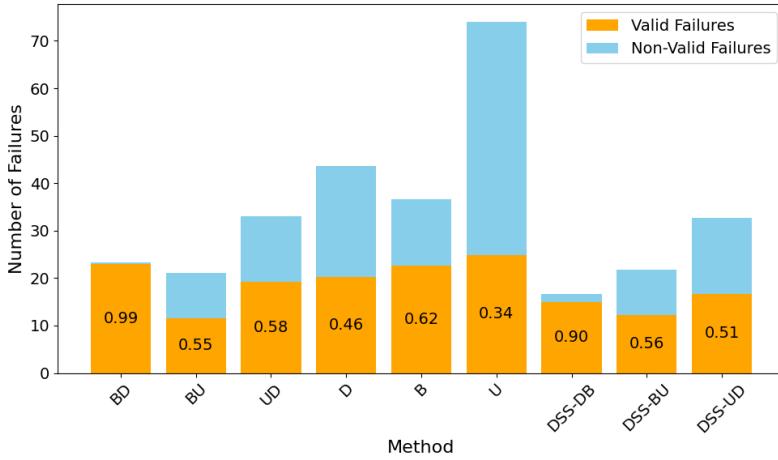
Fig. 5: Validity rate (*valid_rate*) and number of valid failures (*n_valid*) identified for `MultiSim`, `DSS` and `SingleSim` averaged over 10 runs. The average validity rate is shown in each bar plot.

Laptop with an i7 CPU, 32 GB RAM, and a 790 GX GPU. To accelerate DNN computations we used CUDA 11.8 with cuDNN 8.9. Note, that due to simulator-specific requirements a considerable effort was required to identify a hardware configuration which was able to support our case study. BeamNG exhibited initially a very low FPS number when running on a device with the GPU 4090 Ti. In addition, BeamNG does not officially support the Linux OS, but runs on Windows. Udacity, in contrast, could not run on our Windows machine, so that we had to employ a second computing device, i.e., a Linux laptop, to perform the experiments for the BU configuration. Finally, we made sure that all simulators had an average of 20 FPS.

Overall, our experiments required approximately 540 hours i.e., $\approx$ 22 days (10 repetitions $\times$ 9 methods $\times$ 6 hours) for all compared test generation approaches. Additional approximately 84 hours were required to validate 304 failing tests.

5.7 Results

5.7.1 Effectiveness (RQ$_1$)

The results for RQ$_1$ are shown in Figure 5. The figure depicts the average number of failures and the number of *valid* failures, identified from 10 runs for `MultiSim`, `SingleSim` and `DSS`. In addition, in each bar plot the validity rate is annotated in the orange bar.

Number of (valid) failures. `SingleSim` identifies for all simulator configurations more failures than multi-simulators approaches. However, the highest

Table 2: Effectiveness: Statistical tests (Wilcoxon and Vargha-Delaney) for the comparison between `MultiSim` and `SingleSim`, as well as between `MultiSim` and `DSS` for the metrics validity rate and number of valid failures. The letter L represents a large effect size magnitude, M represents a Medium effect, and S represents a small effect (repeated comparisons are excluded (N/A)). Effect values are annotated with a star, if the first approach of the comparison yields lower values then the compared approach.

| | U | B | D | BU | UD | DSS-BD | DSS-BU | DSS-UD |
	p (effect)	p (effect)	p (effect)	p (effect)	p (effect)	p (effect)	p (effect)	p (effect)
BD								
valid_rate	$\sim$**0** (L)	$\sim$ **0** (L)	$\sim$ **0** (L)	**0.01** (L)	$\sim$ **0** (L)	0.72 (-)	$\sim$**0** (L)	$\sim$**0** (L)
n_valid	1.00 (-)	0.85 (-)	0.83 (-)	**0.03** (L)	0.77 (-)	**0.04** (M)	0.06 (-)	0.09 (-)
BU								
valid_rate	0.11 (-)	0.77 (-)	0.43 (-)	N/A	0.77 (-)	**0.02** (L*)	0.77 (-)	0.56 (-)
n_valid	**0.04** (L)	**0.01** (L)	0.16 (-)	N/A	0.11 (-)	0.56 (-)	0.32 (-)	0.14 (-)
UD								
valid_rate	**0.03** (L)	0.92 (-)	0.32 (-)	N/A	N/A	0.08 (-)	0.56 (-)	0.32 (-)
n_valid	0.85 (-)	0.77 (-)	0.68 (-)	N/A	N/A	0.28 (-)	0.38 (-)	0.37 (-)

number of valid failures is found by a `SingleSim` approach (i.e., `SingleSim` on Udacity, U) which is comparable to the number of valid failures identified by the best `MultiSim` approach, i.e., BD. `DSS` identifies, for all simulators configurations, less failures than `MultiSim`, which is similar to the number of valid failures. Simulator-wise, BD identifies significantly less failures than the respective single-simulator configurations, i.e., B and D, but more failures than `DSS`-BD. The number of valid failures is however similar for BD, B and D. The number of failures of BU is similar to the `SingleSim` counterparts, i.e., B and U, however BU has significantly less valid failures than B and U. The results for DSS-BU are comparable to those of BU. For UD the same considerations hold we made for BD.

Validity Rate. The results in Figure 5 show that BD achieves a validity rate of 99%, which is the highest rate across all compared approaches and configurations. BU has a validity rate of 55%, which is surpassed by B, being close to that of DSS-BU. For UD the validity rate is higher compared to those of D, U, and DSS-UD.

We further analyzed the convergence of `MultiSim` and `SingleSim` by using the Hypervolume quality indicator (HV). HV is a well-applied metric in the search-based software engineering domain that measures how optimal and spread is the resulting solution set, allowing to compare Pareto-based optimization approaches [50,51] and assess its convergence. The results, which are available in our replication package [84], show that HV values for `SingleSim` stabilize over time, while those of `MultiSim` achieve values close to those for `SingleSim`, while slightly increasing over time. This indicates that running `SingleSim` longer will likely not improve their effectiveness.

Statistical Tests. We use the non-parametric pairwise Wilcoxon rank sum test (significance level 0.05) and the Vargha Delaney's A_{12} effect size to

compare the *valid_rate* and the *n_valid* values shown in Figure 5. We adopt the following standard classification for effect size values: an effect size e is small, when $0.56 \leq e < 0.64$ or $0.36 < e \leq 0.44$, it is medium when $0.64 \leq e < 0.71$ or $0.29 < e \leq 0.36$ and large when $e \geq 0.71$ or $e \leq 0.29$. Otherwise, the effect size is negligible. The results are shown in Table 2.

The statistical test results show that BD yields significantly higher validity rates with large effect sizes than `SingleSim`, `MultiSim` and `DSS` approaches DSS-BU and DSS-UD. As for BU, the validity rate results for `MultiSim` are in general not better or worse than `SingleSim` or `MultiSim`. For UD, the results are only significant compared to `SingleSim` with Udacity (i.e., U). Regarding the number of valid failures, we see that BD outperforms `DSS`-BD with a medium effect size, while having a similar validity rate. Regarding BU, `SingleSim` B and U are significantly better than BU with a large effect size, what is consistent with the results in Figure 5. Concerning UD, we do not observe a statistical significant difference w.r.t. `SingleSim` and `DSS`.

RQ_1 (effectiveness). `MultiSim` identifies, on average, over all simulator configurations, 70% valid failures, followed by `DSS` (65%) and `SingleSim` (47%). In particular, the multi-simulator configuration BD (BeamNG and Donkey) significantly outperforms the configurations UD (Udacity and Donkey) and UB (Udacity and BeamNG) achieving an average validity rate of 99% failures and identifying 23 simulator-agnostic failures. BD outperforms `SingleSim` and multi-simulator based testing approaches in all configurations beside DSS-BD, where it achieves a comparable validity rate but with a significantly higher number of failures.

5.7.2 Efficiency (RQ₂)

The efficiency results are shown in Table 3. The results show the ratio of the search budget and its standard deviation when the first valid failure is detected. We observe that all `MultiSim` configurations exhibit higher percentages for the first valid failure compared to `SingleSim`, as expected. Compared to `DSS`, we see that the configuration BD achieves a better result than DSS-BD. However, across all configurations, the standard deviations for `MultiSim` are higher than those of `SingleSim` or `DSS`. The combination UD is surpassed by `SingleSim` and `DSS` approaches, beside DSS-BD which yields a higher search time. For BU we can observe a similar behavior.

The statistical test results are shown in Table 4. While D significantly outperforms DB, DB significantly performs better then DSS-DB. Regarding BU, we can only observe that it is outperformed by DSS-BU and D, while there is no significant difference with the other approaches. The configuration UD yields also significant lower search times then U and D, with large effect sizes. However, we do not observe a statistical significant difference w.r.t. DSS-UD, which confirms our observations from Table 4.

Table 3: Efficiency results, i.e., time to first valid failure (in percentage w.r.t. the search budget).

Method	Ratio Budget	Std Dev
BD	39.7	22.9
UD	35.3	24.0
BU	55.6	29.4
U	22.8	16.1
B	25.5	11.3
D	22.4	14.1
DSS-BD	56.6	16.3
DSS-UD	39.9	13.6
DSS-BU	33.5	13.2

Table 4: Efficiency. Statistical tests (Wilcoxon and Vargha-Delaney) for identifying the first valid failure (repeated comparisons are excluded (N/A)). Effect measure values are annotated with a star, if the first approach of the comparison yields lower values then the compared approach.

	U	B	D	UD	BU	DSS-BD	DSS-BU	DSS-UD
	p (effect)	p (effect)	p (effect)	p (effect)	p (effect)	p (effect)	p (effect)	p (effect)
BD								
	0.11 (-)	0.06 (-)	**0.03** (L)	0.70 (-)	0.16 (-)	**0.01** (L*)	0.38 (-)	1.00 (-)
BU								
	0.16 (-)	0.28 (-)	**0.04** (M)	0.19 (-)	N/A	0.85 (-)	**0.03** (L)	0.16 (-)
UD								
	0.03 (L)	**0.02** (L)	**0.01** (L)	N/A	N/A	**0.01** (L*)	0.92 (-)	0.49 (-)

Figure 6 shows the study results considering both effectiveness and efficiency (validity rate vs. search budget required for first valid failure) for `MultiSim`, `SingleSim` and `DSS`. Particularly, the methods whose values are non-dominated either in effectiveness nor efficiency are BD, B and D (Pareto-optimal solutions). `SingleSim`, when using BeamNG and Donkey, is more efficient in finding the first valid failure, while based on the results of the `MultiSim` combination BD, `MultiSim` is significantly more effective.

> RQ$_2$ (efficiency): In two out of three simulator configurations (BD and BU), `MultiSim` demonstrates efficiency comparable to `SingleSim`. Compared to multi-simulator based testing, in the BD configuration, `MultiSim` achieves significantly better results than `DSS`. However, when considering BU, DSS-BU outperforms `MultiSim`.
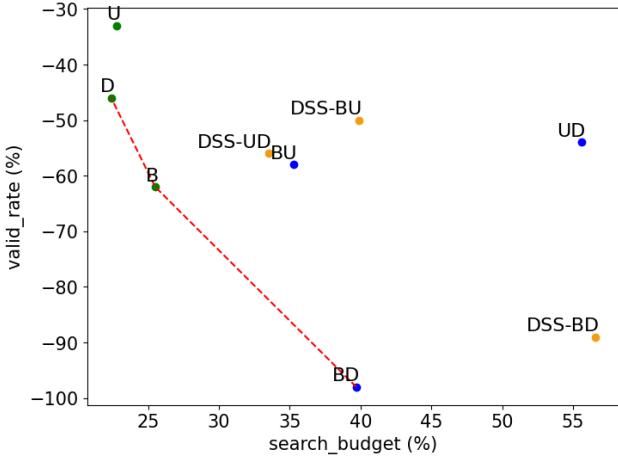
Fig. 6: Visualization of the tradeoff between efficiency (first valid failure) and effectiveness (*valid_rate*) for `MultiSim`, `DSS` and `SingleSim` for different configurations. The Pareto front is visualized in dashed red. Validity rate values are negated, to visualize the Pareto front in the bottom left part of the Figure.

5.7.3 Prediction RQ₃

We selected the best performing `MultiSim` configuration, i.e., BD, to be extended to support prediction of disagreements. In particular, we selected all test cases from 5 completed runs with BD and 5 additional search runs with a modified version of `MultiSim` that focuses on disagreements (Section 5.3). In total, we collected a dataset of 580 agreements and 572 disagreements, which we used to train 5 classification models in predicting disagreements.

The results of the 5-fold cross-validation, using an 80:20 training-to-test split for the trained classifiers, are presented in Table 5. DT represents Decision Tree, RF represents Random Forests, SVM represents Support Vector Machine, LREG stands for Logistic Regression, and GBOOST stands for Gradient Boosing. From all trained classifiers, we select the best performing classification model according to the metrics of Accuracy, F-1 Score and AUC. We identify the RF model as the best classifier and integrate it into `MultiSim` to predict disagreements as described in Section 5.3. As uncertainty threshold we select 70%.

Effectiveness. The boxplots for the *valid_rate* and *n_valid* metrics averaged over 10 runs are shown in Figure 7. The corresponding statistical test results are as follows: regarding the *n_valid* metric, we identify, for the comparison BD vs. BD-P (i.e., the `MultiSim` version of the BD configuration but with the disagreements predictor), a p-value of 0.046 with a large effect size. While the difference is significant, we can see from Figure 7 that the median *valid_rate* is still above 90%. As for *n_valid*, we do not observe a statistically significant difference as the comparison yields a p-value of 0.76 with a medium
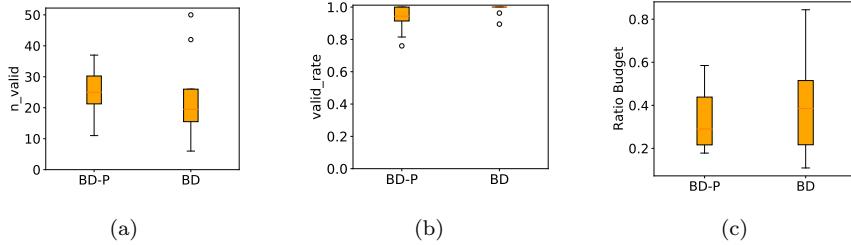
Fig. 7: Effectiveness (a,b) and Efficiency results (c) of `MultiSim` with disagreements prediction averaged over 10 runs. BD-P indicates `MultiSim` with disagreements prediction while BD indicates the original `MultiSim` approach.

effect size. However, from Figure 7 we see that the median value is by 5 failures higher than that of BD-P.

Table 5: Classifier results after 5-fold cross-validation in percentages for predicting disagreements in the simulator configuration BD. Average values are reported with standard deviations in brackets. The best results are marked in bold.

Model	Accuracy	Precision	F1 Score	AUC
DT	78 (2)	78 (4)	79 (1)	78 (2)
RF	**83 (1)**	**82 (3)**	**83 (1)**	**89 (2)**
SVM	62 (2)	58 (2)	69 (2)	71 (4)
LREG	58 (4)	58 (5)	57 (4)	62 (4)
GBOOST	80 (3)	78 (3)	80 (3)	87 (3)

Efficiency. The boxplot results comparing the efficiency of BD-P and BD are shown in Figure 7c. BD-P requires on average less time, i.e., 33% of the search budget compared to BD that finds the first valid failures after 39% of the available search budget. Additionally, we can observe that the standard deviation of BD-P is smaller (14.2%) compared to that of BD (22.9%). However, the statistical test results yield a p-value of 0.49, which shows no significant differences between the two approaches.

> RQ$_3$ (prediction): Among all trained classification models for predicting simulator-related disagreements in simulation outcomes, Random Forest performs best, achieving an AUC score of 0.89 and an F1 score of 0.83. Integrating a classification model into `MultiSim` to bypass simulations leads to a higher median, average and lower standard deviation of simulator-agnostic failures compared to conducting the search without the disagreements predictor.
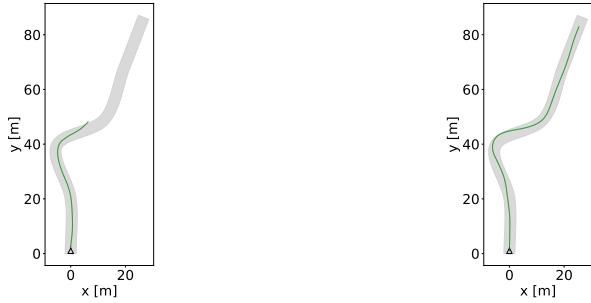
Fig. 8: Example of a disagreement scenario. Left: Vehicle simulated in BeamNG leaves short segment heading towards following segment. Right: Vehicle simulated in Donkey stays within the lane.

5.8 Qualitative Analysis

In the following, we describe a qualitative analysis concerning our evaluation results. In the first part, we highlight disagreement scenarios encountered with `MultiSim`. In the second part, we report on the observations we made regarding results using the disagreement classifier from RQ$_3$.

5.8.1 Disagreements

We manually analyzed the disagreements found by `MultiSim` across different configurations. We made following observations:

(Observation 1) In the BeamNG simulator, occasionally, the vehicle switches to the left lane whenever the underlying segment was short, i.e., < 15m, and the following segment was a left turn (Figure 8). The car continues driving on the left lane towards the next segment, incurring in a failure. This behaviour could be explained by the fact that the vehicle observes the upcoming segment, and considers this shortcut as the immediate straight continuation of its path. However, in Donkey, the vehicle stays in the right lane, even when driving on the same short segment.

(Observation 2) In the BeamNG simulator, the vehicle switches to the left lane in the last but one segment after meeting a sharp curve. This behaviour might be related to the fact that the road terminates after the last segment. However, we did not observe a similar behaviour for the vehicle in the Donkey or Udacity Simulator, which might be attributed to the visualization/rendering differences in the simulators.

5.8.2 Feature Maps of Prediction-based Search

When evaluating the results of `MultiSim` augmented with the prediction classifier, we inspected the feature maps before failure validation. We could observe
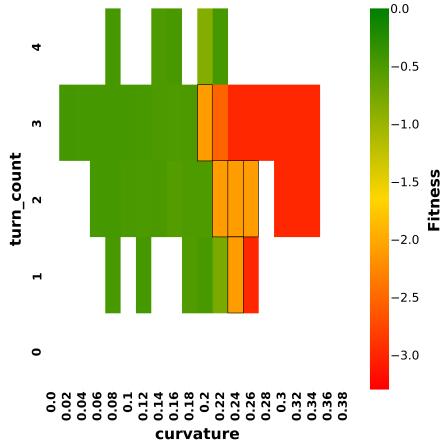
26

Fig. 9: Feature map of tests found in one run with `MultiSim` employing disagreement classifier (BD-P). Cells containing roads for which disagreements are predicted are marked in orange with a black box.

that disagreements are predicted in regions which are between failing and non-failing cells of the map, as shown in Figure 9. Cells that contain tests that are predicted as disagreements by the classifier are marked as orange. This observation highlights the fact that our classifier is likely to perform accurately in predicting disagreements, as it is predicting disagreement on test cases which lie on the boundary between scenarios/roads that pass and fail.

6 Discussion

In this section, we discuss implications, insights and limitations related to our results.

Approach. While our study utilizes two simulators in the ensemble, `MultiSim` can be extended to incorporate a larger number of simulators. To reach consensus on the criticality, we suggest to use an odd number of simulators. Further, the feasibility of the approach with multiple simulators is basically constrained by the underlying computational resources. To mitigate this, test executions in `MultiSim` with multiple simulators might be parallelized, independent of the underlying test algorithm used.

Lessons Learned. Our case study shows that employing multiple simulators in the search does improve the effectiveness of finding simulator-agnostic failures compared to single-simulator testing. However, in the literature, test case generation approaches in general report the evaluation results which are based on single-simulator executions. We suggest that failures found *during* the test

generation or at least the final identified failures, should be evaluated in a second simulator to assess whether the failures are likely to be simulator-agnostic.

Root Cause Analysis. Our paper proposes a testing technique to identify failing test cases where simulators agree on. It is out of the scope of this study to investigate the underlying root causes of disagreements between simulator executions, as it would likely require to inspect, debug, and profile the simulator's code (in Section 5.8 we qualitatively analyzed two disagreement scenarios). Additionally, as outlined in RQ$_3$, the `MultiSim` approach can be configured to search for tests on which simulators disagree to support the identification of the root causes behind failures. As shown by Jodat et al. [40] and Ben Abdessalem et al. [1], decision trees or decision rules can be then applied on underlying roads and simulation traces to derive conditions on input variables and analyze the root causes behind inconclusive and simulator-specific failures.

Among the possible explanations for the disagreements, we conjecture that variations in vehicle dynamics may have influenced our results. Specifically, we observed that the vehicle in Udacity exhibited reduced steering capability compared to those in Donkey and BeamNG. This could account for the high number of simulator-specific failures in Udacity and explain why Udacity appeared more reliable for independent validation (in BD) than during the multi-simulator search, where it introduced spurious failures. As actionable feedback, we recommend incorporating or explicitly detailing vehicle characteristics [65] in scenario definitions for future scenario-based ADAS testing.

Validation. In our study, the validation was dependent on three hyperparameters: the number of re-executions, the failure rate threshold, and the number of failures selected per cell. We set the failure rate threshold to 100%. However, in practice, the threshold for the validation can be configured based on the number of simulators used. We expect that the more diverse simulation environments are employed, the more difficult would be to achieve failure rates of 100%. Regarding the number of re-executions we suggest to perform preliminary experiments with a different number of re-executions and compare the results, as conducted in our study. To select the number of selected failing tests per cell, we carried out preliminary experiments with a higher number of failures, i.e., 5. However, we did not observe significantly different evaluation results. Moreover, we did not select more tests per cell because the feature map already discretizes the search domain, making the diversity of roads within a single cell being likely low.

7 Threats to Validity

External validity is related to the generalizability of our results. We have evaluated `MultiSim` on a well known case study, a DNN trained for lane keeping, employing different simulator pairs from a selected set of different simulators (BeamNG, Donkey and Udacity). It would be interesting to analyze whether the results apply for other case studies, e.g., including automated emergency

braking system in scenarios where other actors are deployed. However, aligning the scenarios, visual appearance, and simulation conditions across simulator with other actors poses a challenge compared to the lane-keeping ADAS case study. Another threat is related to the usage of one ADAS in our evaluation, given its high computational cost (more than 22 days for test generation and validation). Results might not transfer to other ADAS models. However, DAVE-2 is a popular and reliable model across virtual and real-world testing [77, 78], and we mitigated the threats related to an insufficiently trained models with our preliminary evaluation.

Internal validity risks refer to confounding factors. To mitigate confounding factors, we have taken several mitigation strategies. First, to avoid a biased evaluation because of unaligned deployment conditions, i.e., major deviations in communication delays between the SUT and the simulator, we have performed a preliminary assessment/validation of the XTE variation for manually defined driving scenarios across the simulators. Second, we made sure that scenario/road simulation is aligned across simulators building our study upon existing research [12]. Third, we have defined a condition when generated roads are considered as invalid, and have regenerated after mutation roads when they are invalid.

To evaluate the BU setup, we have executed each simulator on different hardware configurations, because of simulator-system incompatibilities (Udacity did not run on Windows, but BeamNG only runs on Windows). This fact might have influenced BU results. However, the BU configuration did not yield a superior performance compared to approaches highlighted in our results.

Further, to make sure that we identify simulator-agnostic failures we validated identified failures after the test generation process of `MultiSim`, `DSS` and `SingleSim` on one or two simulators which has been left-out during the search. In addition we re-ran failing tests multiple times to filter out failures identified because of a flaky simulation environment.

Construct validity threats relate to the inappropriate use of metrics. To evaluate the performance of `MultiSim` and compared approaches we have used two metrics: the number of simulator-agnostic failures, and the validity rate, i.e., the ratio between simulator-agnostic failures and validated failures. The first metric is a default metric used to assess the performance of test case generation approaches [43]. The choice of the second metric is motivated by the fact that, when using a test generator, the tester is interested in knowing how many of the generated failures are simulator-agnostic. In addition, we analyzed the convergence of the HyperVolume metric applied to `MultiSim` and `SingleSim`, which indicates that running longer `SingleSim` search will not improve effectiveness results. We did not evaluate the convergence of `DSS` as it is not a Pareto-based optimization approach.

To foster *replicability*, the implementation of `MultiSim`, as well as results of the evaluation for `MultiSim`, `SingleSim` and `DSS` are available online. The search approach and the analysis of the results have been implemented using the modular and open-source search-based testing framework OpenSBT [74],

which allows to integrate other case studies to be tested with `MultiSim`, `SingleSim` and DSS.

8 Related Work

In this section, we outline two categories of related work. The first category targets ADAS testing approaches that use one simulator for test generation. The second category reports studies that employ multiple simulators for testing.

8.1 Single-Simulator Approaches for ADAS Testing

Most current test generation methods use search-based approaches to automatically create test cases for DNN-driven ADAS systems [1, 2, 10, 41, 60, 67, 69, 83, 91]. In this domain, test cases consist of individual driving images or road topologies, which are rendered through a driving simulator. Abdessalem et al. [1,2,10] integrate genetic algorithms with machine learning techniques to test a pedestrian detection system. Mullins et al. [63] apply Gaussian processes to guide search-based test generation toward unexplored regions within the input space. Gambi et al. [29] leverage procedural content generation to propose a search-based test generation approach for ADAS. Riccio and Tonella [69] introduce, a model-based test generator that leverages Catmull-Rom splines, the test representation as used in our approach, to define road shapes, producing test cases at the behavioral frontier of self-driving car models. Arrieta et al. [6] apply a genetic algorithm to generate tests for cyber-physical systems, optimizing them across three dimensions: requirement coverage, test case similarity, and execution time. Lastly, Lu et al. [55] employ reinforcement learning to discover environmental configurations that induce crashes. DeepQTest [56] is a testing approach that uses reinforcement learning to learn environment configurations with a high chance of revealing ADAS misbehaviors. In another work [54], epigenetics algorithms are used to test ADAS in dynamically changing environments.

Among the fuzzing domain, DriveFuzz [42] leverages the physical state of the vehicle, along with oracles grounded in real-world traffic rules, to guide the fuzzer toward uncovering potential misbehaviors. AutoFuzz [92], on the other hand, focuses on fuzzing the test scenario specifications. Before initiating the fuzzing process, it employs a seed selection mechanism using a binary classifier that identifies seeds with a higher likelihood of violating traffic rules. AV-Fuzzer [49] applies a genetic algorithm, informed by the positioning of globally monitored non-player characters (NPCs) within each driving scenario. NPCs deemed to have a higher likelihood of safety violations [39] are prioritized for evolution. Cheng et al. [21] introduce BehaviorMiner, an unsupervised model that extracts temporal features from predefined scenarios and employs clustering-based abstraction to group behaviors with similar features into abstract states.

All these approaches use a single-simulator approach, with some works validating their propositions on multiple simulators [21], for example, because different ADS are compatible/integrated only with specific simulation platforms [65]. Our approach differs from these solutions because it uses an ensemble of simulations during search-based testing to retrieve more accurate fitness signals, based on the consensus among the simulators.

8.2 Multi-Simulator Approaches for ADAS Testing

A study by Borg et al. [16] investigates the comparability of multiple simulators for testing a pedestrian vision detection system. The study evaluates a large set of test scenarios on both PreScan [72] and Pro-SiVIC [32]. The study reports inconsistent results in terms of safety violations and behaviors across these simulators. Consequently, the authors suggest that a single-simulator approach for ADAS testing might be unreliable, especially when failures are highly dependent on the chosen simulator. Moreover, a recent study by Amini et al. [5] has analyzed the degree of flakiness affecting ADAS testing. The study evaluates several simulators and ADAS showing that test flakiness is common and can significantly impact the test results. The authors propose the usage of machine learning classifiers to identify flaky ADAS tests. Another study by Wagner et al. [88] evaluates the translation of real-world driving scenarios to executed scenarios in a simulator. Their results show that a reprocessing error exists, which can be basically attributed to sensor model offsets and can be tackled by employing scenario-based sensor models.

To address simulator disagreements, Biagiola et al. [12] involve search-based testing across multiple simulators, provided that the same test scenario and ADAS under test can be consistently represented. Their method combines the predicted failure probabilities from each simulator, reporting a failure only when there is consensus among the simulators. In this method, the search process is conducted separately for each simulator, which can lead to numerous simulator-specific failures. Since discrepancies between simulators are only addressed after the searches terminate, this can lead to unnecessary consumption of the testing budget when such failures occur.

Following the approach of Biagiola et al. [12], we also base our methodology on multi-simulator, search-based testing, leveraging simulators capable of accommodating analogous configurations in terms of test scenarios and ADAS. However, our approach differs by performing a joint test evaluation *during the search*, ensuring that scenarios leading to simulator-dependent failures (i.e., simulator disagreements) are filtered out before progressing further.

9 Conclusion and Future Work

In this paper, we presented the approach `MultiSim`, to mitigate simulator-specific failures when testing ADAS using an ensemble of simulators. Our

approach leverages search-based testing and executes test inputs in multiple simulators during the search to identify generalizable failures.

In our empirical study, we evaluated our approach on testing a DNN-enabled ADAS trained for lane-keeping. We compared our approach in terms of effectiveness and efficiency in identifying simulator-agnostic/valid failures, to single-simulator based testing as well as state-of-the-art testing approach which employs multiple simulators. The results of the study show that combining evaluation results from multiple simulators during testing outperforms single-simulator testing, identifying nearly 100% valid failures. Compared to existing multi-simulator approaches, `MultiSim` identifies, on average, more valid failures. In terms of efficiency, `MultiSim` performs similarly to other approaches. Additionally, the study demonstrates that machine learning can be used within `MultiSim` to predict disagreements between test outcomes across different simulators, increasing efficiency and reducing the variation in the number of valid failures.

Our future work is to extend our study to other use cases including more complex systems under tests such as full-stack ADAS and to investigate the root causes behind the disagreements of evaluation outcomes.

10 Declarations

10.1 Funding

10.2 Ethical Approval

Not applicable.

10.3 Informed Consent

Not applicable.

10.4 Author Contributions

Lev Sorokin: conceptualization, methodology, implementation, evaluation, writing, review, editing. **Matteo Biagiola**: conceptualization, methodology, review, editing. **Andrea Stocco**: conceptualization, methodology, review, editing.

10.5 Data Availability Statement

All our results, the source code, and the simulator are accessible and can be reproduced [84].

10.6 Conflict of Interest

The authors declare no conflict of interest.

10.7 Clinical Trial Registration

Clinical trial number: Not applicable.

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